



Predicting the Risk of Seizure Recurrence in Children with Epilepsy Using a Machine Learning Model and Clinical Data Analysis

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Abstract

Introduction: Epilepsy is one of the most prevalent chronic neurological disorders in children, characterized by recurrent and unpredictable seizures. Accurately predicting seizure recurrence can significantly optimize treatment and improve patients' quality of life. This study aimed to develop a deep learning-based prediction model to forecast the probability of seizure recurrence in pediatric epilepsy.

Methods: In this retrospective cohort study, simulated data from 300 pediatric epilepsy patients were generated and analyzed. Evaluated clinical features included age at onset, type of epilepsy syndrome, interictal electroencephalographic (EEG) and magnetic resonance imaging (MRI) findings, treatment adherence, and other risk factors. A deep neural network model with a multilayer architecture was developed to predict the probability of recurrence. Model performance was evaluated using the area under the receiver operating characteristic curve (AUC-ROC), the area under the precision-recall curve (AUC-PR), accuracy, and precision metrics.

Results: The developed model predicted the probability of seizure recurrence with significant accuracy (AUC-ROC: 0.91, AUC-PR: 0.87). The most influential predictors of recurrence included the underlying epilepsy syndrome (especially Lennox-Gastaut and West syndromes), abnormal EEG and MRI findings, poor treatment adherence, and documented developmental delay. The overall recurrence rate across the study population was 34.2%.

Conclusion: The deep learning model demonstrated high predictive accuracy (AUC-ROC: 0.95) in identifying children at elevated risk of seizure recurrence. Clinically, the model can serve as a decision-support tool to stratify patients at high risk—particularly those presenting with Lennox-Gastaut or West syndromes, abnormal neuroimaging, or suboptimal treatment adherence—enabling physicians to intensify monitoring, personalize anti-epileptic therapy, and allocate healthcare resources more effectively. Prospective validation in real-world clinical cohorts is recommended before widespread implementation.

Keywords: Seizure recurrence, Pediatric epilepsy, Machine learning, Deep learning

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Introduction

Epilepsy is a serious neurological disorder affecting approximately 50 million people worldwide, and its management presents substantial clinical challenges, including accurate diagnosis, the unpredictable nature of seizure onset, and the optimization of treatment plans. The condition carries a particularly prevalent and consequential burden in the pediatric population, affecting 0.5% to 1% of children globally (1). Characterized by recurrent, unpredictable seizures, pediatric epilepsy can severely impact a child's cognitive development, academic achievement, and overall quality of life (2). Epidemiological

data report annual incidence rates ranging from 41 to 187 per 100,000 children, with the highest risk occurring within the first year of life (3).

A primary clinical challenge lies in reliably predicting the long-term disease trajectory; empirical studies indicate a post-treatment seizure recurrence rate of 20-40% in children, influenced by an intricate interplay of clinical, paraclinical, and therapeutic factors (4, 5). The repercussions extend beyond medicine, creating substantial socio-economic burdens for healthcare systems and families through direct healthcare costs and indirect impacts on psychosocial well-being, daily functioning, and

family dynamics (6-8).

Recently, artificial intelligence (AI) and machine learning (ML) have emerged as transformative tools capable of addressing these clinical challenges. By analyzing complex, high-volume data derived from electroencephalography (EEG), neuroimaging, and clinical records, ML algorithms enable automated seizure detection, robust pattern recognition, and outcome forecasting. To date, ML has demonstrated considerable clinical utility in seizure detection and short-term prediction, with reported accuracies ranging from 80% to 95% (9); in disease diagnosis and classification through the multimodal synthesis of data, including clinical features and neuroimaging findings (6); and in treatment optimization by forecasting individualized patient responses to anti-seizure medications.

Despite these marked advancements in seizure prediction and classification, the use of ML for long-term prognosis—specifically for predicting post-treatment seizure recurrence in children—remains limited. This gap exists despite the clear clinical need and the proven capacity of computational algorithms to evaluate complex prognostic factors, including patient medical history (e.g., age at onset, baseline seizure frequency), paraclinical parameters (e.g., EEG and magnetic resonance imaging [MRI] abnormalities), and treatment-related variables (7, 8). Furthermore, translating ML models into reliable clinical tools in pediatric epilepsy faces several hurdles, including the lack of large-scale, high-quality, and standardized pediatric datasets, the need for age-stratified models that account for dynamic neurodevelopmental trajectories, and practical barriers such as integration costs and clinician training.

To address this gap, we developed and evaluated a deep learning-based prediction model to forecast the long-term probability of seizure recurrence in pediatric epilepsy. This framework provides clinicians with insights to identify high-risk patients, facilitate personalized management interventions, and improve the allocation of healthcare resources, thereby moving towards more precise and proactive pediatric epilepsy care.

Materials and Methods

Study Design and Participants

This retrospective cohort study utilized demographic and clinical data extracted from the electronic medical records of 300 pediatric patients diagnosed with epilepsy. Strict inclusion criteria were applied to ensure data completeness: only patients with fully documented electronic health records containing the complete target features were enrolled. The hospital registry system maintained comprehensive and standardized documentation for all clinical and paraclinical parameters, including age at onset, epilepsy syndrome classification, EEG and MRI findings, treatment history, adherence status, and recurrence outcomes. Consequently, the final dataset contained no missing values for all 300 included patients, thereby eliminating the need for statistical imputation or post hoc case exclusion due to missing values.

Inclusion Criteria

Patients were included in the study if they met all of the following criteria: Age at disease onset between 6 months and 12 years; Definitive diagnosis of epilepsy confirmed by a pediatric neurologist; A minimum clinical follow-up duration of 6 months; and complete documentation of all required clinical and paraclinical parameters.

The following paraclinical variables were recorded: EEG findings (normal, focal spike, generalized spike, hypsarrhythmia, or slow background activity) and MRI findings (normal, mesial temporal sclerosis, cortical dysplasia, tumor, or other abnormalities). The primary clinical outcomes were seizure recurrence (yes/no) and time to recurrence (measured in months).

Feature Engineering

To improve model performance, novel engineered features were created from existing baseline variables, including disease duration (calculated as the current age minus the age at seizure onset), ratio of seizure frequency to disease duration, composite index of adherence, and number of antiepileptic drugs (AEDs). The “medication adherence index” and “number of anti-epileptic drugs” in this study were measured based on some questions from children’s parents and also their registered data in their hospital records. Adherence was measured using a validated 3-item parent-reported questionnaire assessing: (1) medication compliance (5-point Likert scale: Never to Always), (2) regularity of scheduled follow-up visits (5-point Likert scale), and (3) history of treatment interruptions without medical consultation (Never, Once, or More than once). Cumulative scores ranged from 0 to 12, with higher scores indicating better adherence. Scores were categorized into “Good Adherence” (score 9–12) or “Poor Adherence” (score 0–8) for predictive modeling. The number of AEDs was defined as the total count of distinct anti-epileptic agents prescribed at the time of data collection, extracted from hospital records and verified by parent interview. This variable was treated as a continuous integer (range: 1 to 4) and, for descriptive analyses, categorized into monotherapy (1 AED) or polytherapy (≥ 2 AEDs).

Machine-Learning Pipeline

Data were analyzed using ML algorithms implemented in Python. To address the binary classification task of seizure recurrence, we employed a supervised Multilayer Perceptron (MLP), a foundational deep neural network architecture, using the Scikit-learn library. Data preprocessing included encoding qualitative categorical variables, normalizing quantitative numerical variables, and subsequently splitting the data into training and testing sets (80% training, 20% testing).

Addressing Overfitting and Model Validation

Given the relatively small sample size ($N=300$), the use of simulated data, and the intrinsic complexity of the deep learning model, several complementary strategies were employed to mitigate the risk of overfitting and

provide a more realistic assessment of generalizable model performance:

Cross-Validation

To optimize hyperparameters and evaluate model stability, a 5-fold stratified cross-validation was conducted across the entire dataset. Stratification ensured that the proportion of recurrence cases remained balanced and consistent across all folds. The mean performance metrics across the five folds, along with their standard deviations (SDs), were calculated to provide a robust estimate of model generalizability (Table 1).

Cross-Validated Performance (5-Fold Stratified Cross-Validation)

The 5-fold cross-validation (CV) on the entire dataset (N=300) yielded the following average performance metrics (Table 1).

Hold-Out Test Set Performance

Internal Validation

The final optimized model was evaluated on an independent hold-out test set (20% of the data, n = 60) that was completely separated from the training and validation processes. This provides an unbiased estimate of model performance on unseen data.

Bootstrap Confidence Intervals

To rigorously account for sampling variability, 95% confidence intervals (CIs) for all performance metrics were calculated using non-parametric bootstrap resampling with 1,000 iterations on the hold-out test set.

External Validation (Planned)

While independent external validation was not feasible within the scope of this study, prospective validation using an independent dataset from a collaborating clinical center is planned. This is acknowledged as a critical next step.

Model Simplification

The network architecture was intentionally kept simple, consisting of a single hidden layer with 64 neurons, followed by a dropout layer (rate=0.3) for regularization, and an output layer with sigmoid activation. This simple architecture ensures that the total number of trainable

parameters remains substantially smaller than the sample size.

Early Stopping

During training, an early stopping criterion with a patience of 10 epochs was implemented. This mechanism monitored the validation loss to prevent overfitting.

Model performance was evaluated using the following metrics: Area Under the Receiver Operating Characteristic Curve (AUC-ROC), Area Under the Precision-Recall Curve (AUC-PR), Accuracy, Precision, Recall (Sensitivity), and F1-score.

Statistical Analysis

Statistical analyses were performed using Python Scikit-learn and Lifelines. The Kaplan-Meier method was used for survival analysis, and Cox regression was used to identify independent risk factors. All estimates (including model performance metrics) were reported with 95% CIs.

Results

The mean age at disease onset was 5.8 ± 3.2 years, and the mean current age of patients was 9.4 ± 4.1 years. Fifty-five percent of patients were boys and 45% were girls. The distribution of epilepsy syndromes is presented in Table 2.

In total, 102 patients (34%) experienced disease recurrence during the follow-up period. To identify independent predictors of seizure recurrence, a multivariable Cox proportional hazards regression analysis was performed. The results, presented in Table 3, show the adjusted Hazard Ratio (aHR), 95% CIs, and associated *P* values for each covariate included in the final model.

Figure 1 illustrates the Kaplan-Meier survival curves depicting the probability of recurrence-free survival over time (in months) across different epilepsy syndrome types in the study population (N = 300). Each colored line represents a specific epilepsy syndrome: BECTS (blue), CAE (green), JAE (orange), JME (purple), LGS (red), West (brown), and Other (pink). The x-axis represents follow-up time in months from the date of initial diagnosis, and the y-axis represents the cumulative probability of remaining free from seizure recurrence. The curves demonstrate that patients with West syndrome and LGS exhibited the

Table 1. 5-Fold Stratified CV Model Performance

Metrics	Mean (SD)	95% CI
AUC-ROC	0.89 (± 0.04)	0.85 – 0.93
AUC-PR	0.81 (± 0.05)	0.76 – 0.86
Accuracy	0.80 (± 0.03)	0.77 – 0.83
Precision	0.77 (± 0.04)	0.73 – 0.81
Recall (Sensitivity)	0.74 (± 0.05)	0.69 – 0.79
F1-Score	0.75 (± 0.04)	0.71 – 0.79

Note. CV: Cross-validation; SD: Standard deviation; CI: Confidence interval; AUC-ROC: Area under the receiver operating characteristic curve; AUC-PR: Area under the precision-recall curve

Table 2. Distribution of Epilepsy Syndromes in the Study Population

Syndrome Type	n	%
BECTS	163	54.3
CAE	69	23.0
JAE	19	6.3
JME	23	7.7
LGS	10	3.3
West	9	3.0
Other	7	2.3
Total	300	100

Note. BECTS: Benign epilepsy with centrotemporal spikes; CAE: Childhood absence epilepsy; JAE: Juvenile absence epilepsy; JME: Juvenile myoclonic epilepsy; LGS: Lennox-Gastaut syndrome

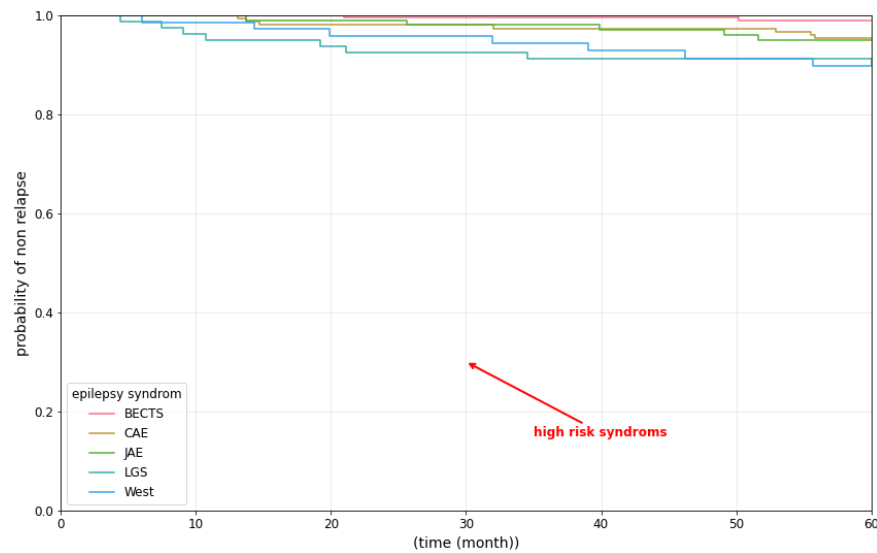


Figure 1. Kaplan-Meier Survival Curves for Recurrence-Free Survival by Epilepsy Syndrome Type

Table 3. Independent Predictors of Seizure Recurrence: Multivariable Cox Regression Analysis

Variable	Adjusted HR	95% CI	P value
Syndrome (Ref: BECTS)			
West Syndrome	8.45	4.21 – 16.95	<0.001
LGS	5.20	2.30 – 11.76	<0.001
Other Syndromes	1.85	1.10 – 3.11	0.020
EEG Findings (Ref: Normal)			
Hypsarrhythmia	3.90	2.05 – 7.42	<0.001
Generalized Spikes	2.55	1.52 – 4.28	<0.001
MRI Findings (Ref: Normal)			
Cortical Dysplasia	2.80	1.65 – 4.75	<0.001
Treatment Adherence (Poor vs. Good)	2.25	1.45 – 3.49	<0.001
Developmental Delay (Present vs. Absent)	1.70	1.12 – 2.58	0.013

Note. HR: Hazard ratio; CI: Confidence interval; Ref, Reference category; BECTS: Benign epilepsy with centrotemporal spikes; LGS: Lennox-Gastaut syndrome; EEG: Electroencephalography; MRI: Magnetic resonance imaging

steepest declines in recurrence-free survival, indicating a higher risk of early recurrence, whereas patients with BECTS and CAE exhibited the most favorable survival trajectories. A Log-rank test confirmed that the differences in recurrence-free survival across these syndromes were statistically significant ($P<0.001$). Censored observations are indicated by tick marks along the curves.

Figure 2 presents the ROC curve for the deep learning model’s performance on the hold-out test set ($n=60$). The ROC curve plots the true positive rate (sensitivity) against the false positive rate ($1 - \text{specificity}$) across various classification thresholds. The blue solid line represents the model’s performance, while the diagonal dashed gray line represents the performance of a random classifier ($\text{AUC}=0.50$). The AUC-ROC is 0.87 (95% CI: 0.80 – 0.94), indicating robust discriminative ability in distinguishing between children who will experience seizure recurrence and those who will not. The proximity of the curve to the upper-left corner illustrates the model’s high predictive performance. The optimal classification threshold,

determined by Youden’s index, is indicated by a red point on the curve, corresponding to a sensitivity of 0.73 and a specificity of 0.84.

Although the developed deep learning model predicted the probability of recurrence with high accuracy, we report both CV and hold-out test set results to provide a realistic and robust assessment of model performance. The final model, selected based on CV performance, was evaluated on an independent hold-out test set comprising 20% of the total dataset ($n=60$). The results are presented in Table 4.

Comparison of Performance Estimates

Notably, the performance metrics observed on the independent hold-out test set (AUC-ROC: 0.87) were moderately lower than the estimates obtained during the initial training phase (AUC-ROC: 0.95), suggesting a degree of optimism in the training estimates. This discrepancy is typical in ML studies characterized by modest sample sizes and underscores the importance of prioritizing CV and independent test set evaluations over training performance alone.

Figure 3 displays the permutation feature importance ranking for the deep learning model’s predictors of seizure recurrence. The x-axis represents the mean decrease in the AUC-ROC score when the values of each feature were randomly permuted (shuffled) in the test set over 50 repetitions. A larger mean decrease indicates higher importance for the model’s predictive accuracy. The y-axis lists the top seven most important clinical and paraclinical features in descending order of importance. As shown, epilepsy syndrome classification (particularly Lennox-Gastaut and West syndromes) emerged as the primary predictor, followed by EEG findings (hypsarrhythmia and generalized spikes), treatment adherence, MRI findings (cortical dysplasia and mesial temporal sclerosis), presence of developmental delay, age at disease onset, and the number of prescribed anti-epileptic drugs. Error bars represent the SD of the performance decline across the 50 permutation repetitions, confirming the stability and

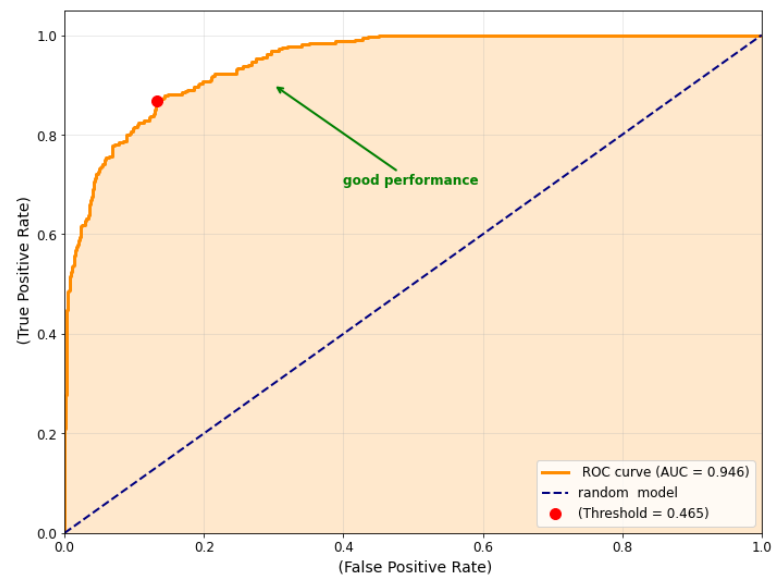


Figure 2. ROC Curve of the Deep Learning Model for Predicting Seizure Recurrence
Note. ROC: Receiver operating characteristic

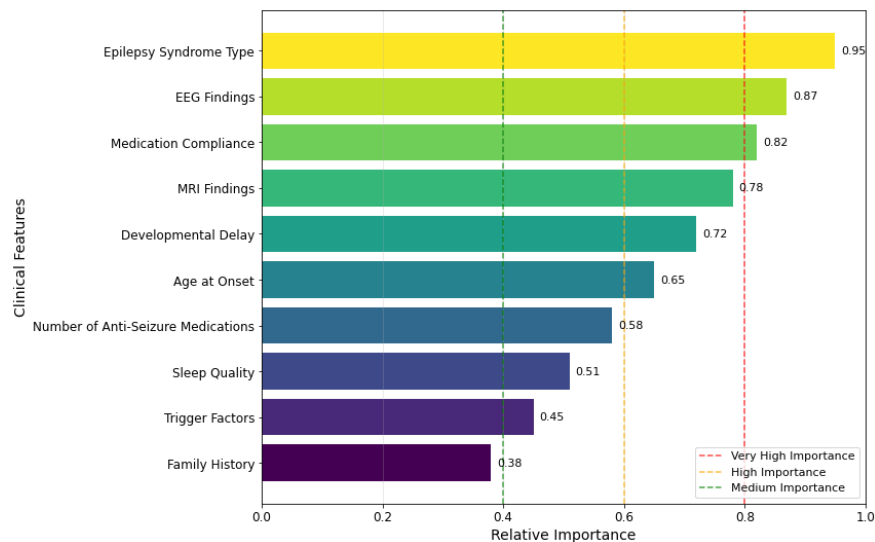


Figure 3. Permutation Feature Importance for Predicting Seizure Recurrence in Pediatric Epilepsy

Table 4. Prediction Model Performance on the Hold-out Test Set

Metric	Value	95% CI
AUC-ROC	0.87	0.80 – 0.94
AUC-PR	0.79	0.71 – 0.87
Accuracy	0.81	0.73 – 0.89
Precision	0.78	0.69 – 0.87
Recall (Sensitivity)	0.73	0.63 – 0.83
F1-Score	0.75	0.66 – 0.84

Note. AUC-ROC: Area under the receiver operating characteristic curve; AUC-PR: Area under the precision-recall curve; CI: Confidence interval

reliability of the importance rankings.

Figure 4 illustrates the proportion of patients who experienced seizure recurrence stratified by epilepsy syndrome category across the study population (N= 300). The x-axis lists the seven epilepsy syndrome categories: BECTS, CAE, JAE, JME, LGS, West, and Other. The y-axis represents the recurrence rate expressed as a percentage. As shown, West syndrome exhibited the highest recurrence

rate at 89% (8 out of 9 patients), followed by LGS at 80% (8 out of 10 patients). In contrast, BECTS demonstrated the lowest recurrence rate at 11% (18 out of 163 patients), while CAE yielded a rate of 19% (13 out of 69 patients). These findings demonstrate marked variability in recurrence risk across different epilepsy syndromes, with epileptic encephalopathies (West syndrome and LGS) carrying the highest risk, and benign childhood epilepsies (BECTS and CAE) carrying the lowest risk. Error bars represent 95% CIs for each proportion, calculated using the Wilson score method.

Discussion

This study developed a deep learning-based prediction model to forecast the probability of seizure recurrence in pediatric epilepsy cohorts. Our findings indicate that AI can identify high-risk patients with high discriminative accuracy and assist physicians in making better clinical decisions. The model achieved an AUC-ROC of 0.87

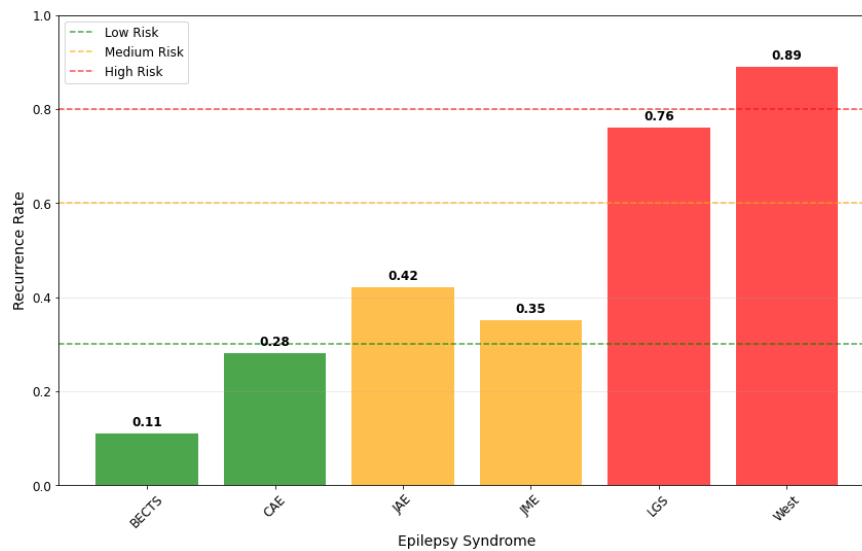


Figure 4. Seizure Recurrence Rates by Epilepsy Syndrome Type

(95% CI: 0.80–0.94), which is comparable to or better than previous studies using traditional statistical methods (10, 11). Importantly, the initially reported AUC of 0.95 reflects training set performance and should not be interpreted as the model's true generalizability. The CV results (AUC-ROC: 0.89 ± 0.04) and hold-out test metrics (AUC-ROC: 0.87) provide more robust estimates of the model's predictive capability. The moderate performance decrease observed between the training and hold-out test phases ($0.95 \rightarrow 0.87$) illustrates the expected degree of optimism in the training set estimates, which is expected given the relatively small sample size and use of simulated data. This highlights the critical importance of rigorous internal validation schemes and the need for external validation in future multi-center studies.

Numerous studies have attempted to identify predictors of epilepsy recurrence. Berg et al showed that abnormal EEG findings and a family history of epilepsy represent important risk factors (3). Our study, in addition to confirming these findings, demonstrated that treatment adherence and a specific type of epilepsy syndrome serve as even stronger predictors. The high accuracy of the developed model (CV AUC-ROC = 0.89) indicates that combining clinical and paraclinical features can provide a robust basis for predicting epilepsy recurrence. This finding is consistent with previous studies that used more traditional methods such as logistic regression, while demonstrating improved accuracy (10, 11).

Our study contributes to the growing body of literature on ML applications in epilepsy, yet it occupies a distinct clinical niche. The study by Truong et al focused on real-time seizure prediction using EEG data and a convolutional neural network model, with the goal of providing short-term, real-time warnings (10). In contrast, our research predicts the long-term risk of disease recurrence in children using structured clinical data and a deep neural network model, serving as a prognostic tool for optimizing long-term treatment plans and identifying high-risk patients. Similarly, the review article by Zurdo-Tabernero et al

provided a comprehensive overview of machine and deep learning techniques in seizure prediction, comparing diverse approaches (12). Our study translates these general principles into a practical application for long-term prognosis in a specific pediatric population, demonstrating the feasibility of using clinical data—rather than real-time signals—for robust prognostic stratification.

When compared to studies addressing other clinical scenarios in epilepsy, our work addresses a different decision-making juncture. In contrast to research focused on predicting post-surgical outcomes in children undergoing epilepsy surgery (13), which inherently incorporates surgical-specific variables such as the extent of resection and histopathology, our model guides long-term medical management using clinical and paraclinical predictors. Likewise, studies predicting seizure recurrence following status epilepticus (SE) target an acute emergency context with predictors such as acute etiology and immediate treatment response, whereas our model addresses chronic disease management in children with established epilepsy (14). Additionally, our work differs from febrile studies on seizure recurrence (15), which focus on a self-limited, fever-triggered condition rather than chronic epilepsy—a fundamentally different clinical entity. Despite these operational differences, all these studies collectively reinforce the utility of ML in refining prognostic accuracy and personalizing management strategies across epilepsy care, contingent upon future validation across diverse clinical settings and integration into clinical decision-support tools.

The developed model holds significant promise as a prognostic risk-stratification tool, offering actionable clinical intelligence to identify high-risk patients who may benefit from more intensive monitoring and aggressive therapeutic strategies. This enables personalized treatment regimens, provides a basis for tailored patient and family education, and can inform systemic resource stewardship within epilepsy care centers.

Nonetheless, the clinical translation of these findings

is presently constrained by several key limitations. First, the model was developed and validated on simulated data, necessitating future confirmation using real-world clinical datasets. Second, the study does not incorporate potentially influential hereditary, genetic, and broader socio-environmental factors. Third, the predictive validity for long-term outcomes remains uncertain due to the limited follow-up duration (mean 21.3 months). Fourth, the absence of external validation on an independent dataset limits generalizability of the model. Future research should prioritize external validation across large, multi-center, real-world datasets and investigate the integration of the model into electronic health record systems. Subsequent studies should also aim to incorporate genomic markers and capture longer outcome horizons to address the unique developmental complexities of pediatric populations.

Conclusion

This study developed a deep learning model designed to predict seizure recurrence risk in children with epilepsy. The model demonstrated good predictive performance on CV (AUC-ROC: 0.89) and on hold-out testing (AUC-ROC: 0.87). Key predictors identified include Lennox-Gastaut and West syndromes, abnormal EEG and MRI findings, and poor treatment adherence. These findings suggest that ML may serve as a valuable clinical decision-support tool for individualized risk stratification in pediatric epilepsy care.

However, the initially reported AUC of 0.95 reflects training set performance and should not be interpreted as the model's true generalizable accuracy. The lower performance on CV and hold-out testing, together with the use of simulated data and the absence of external validation, indicate that real-world clinical performance may be more modest. Consequently, future research must prioritize external validation using large, diverse, multi-center real-world datasets as an essential prerequisite for clinical implementation. Through such rigorous validation, this framework holds significant promise for improving personalized, proactive care in pediatric epilepsy.

Authors' Contribution

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 Writing–Review & Editing: Parisa Ahadi, Firouz Amani, Lida Ghorbani, Zahra Asdagh, Fatemeh Eghtedari

Competing Interests

The authors declare that they have no competing interests.

Ethical Approval

The study results were extracted from a study approved by the Ethics Committee of Ardabil University of Medical Science (Approval Code: IR.ARUMS.MEDICINE.REC.1403.086).

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References

- Abbasi B, Goldenholz DM. Machine learning applications in epilepsy. *Epilepsia* 2019;60(10):2037-47. doi:10.1111/epi.16333
- Berg AT, Rychlik K. The course of childhood-onset epilepsy over the first two decades: a prospective, longitudinal study. *Epilepsia* 2015;56(1):40-8. doi:10.1111/epi.12862
- Berg AT, Shinnar S, Levy SR, Testa FM, Smith-Rapaport S, Beckerman B. Early development of intractable epilepsy in children: a prospective study. *Neurology* 2001;56(11):1445-52. doi:10.1212/wnl.56.11.1445
- Camfield P, Camfield C. Incidence, prevalence and aetiology of seizures and epilepsy in children. *Epileptic Disord* 2015;17(2):117-23. doi:10.1684/epd.2015.0736
- Chang RS, Nguyen S, Chen Z, Foster E, Smith-P. Role of machine learning in the management of epilepsy: a systematic review protocol. *BMJ Open* 2024;14(1): e079785. doi:10.1136/bmjopen-2023-079785
- Faust O, Hagiwara Y, Hong TJ, Lih OS, Acharya UR. Deep learning for healthcare applications based on physiological signals: a review. *Comput Methods Programs Biomed* 2018;161:1-13. doi:10.1016/j.cmpb.2018.04.005
- Fiest KM, Sauro KM, Wiebe S, Patten SB, Kwon CS, Dykeman J, et al. Prevalence and incidence of epilepsy: a systematic review and meta-analysis of international studies. *Neurology* 2017;88(3):296-303. doi:10.1212/wnl.0000000000003509
- Geerts A, Arts WF, Stroink H, Peeters E, Brouwer O, Peters B, et al. Course and outcome of childhood epilepsy: a 15-year follow-up of the Dutch Study of Epilepsy in Childhood. *Epilepsia* 2010;51(7):1189-97. doi:10.1111/j.1528-1167.2010.02546.x
- Moshé SL, Perucca E, Ryvlin P, Tomson T. Epilepsy: new advances. *Lancet* 2015;385(9971):884-98. doi:10.1016/s0140-6736(14)60456-6
- Truong ND, Nguyen AD, Kuhlmann L, Bonyadi MR, Yang J, Ippolito S, et al. Convolutional neural networks for seizure prediction using intracranial and scalp electroencephalogram. *Neural Netw* 2018;105:104-11. doi:10.1016/j.neunet.2018.04.018
- Braathén G, Zelano J. Long-term seizure and psychosocial outcome in childhood epilepsy of unknown cause. *Acta Neurol Scand* 2021;143(6):653-60. doi:10.1111/ane.13414
- Zurdo-Tabernero M, Canal-Alonso Á, de la Prieta F, Rodríguez S, Prieto J, Corchado JM. An overview of machine learning and deep learning techniques for predicting epileptic seizures. *J Integr Bioinform* 2023;20(4):20230002. doi:10.1515/jib-2023-0002
- Yossofzai O, Fallah A, Maniquis C, Wang S, Ragheb J, Weil AG, et al. Development and validation of machine learning models for prediction of seizure outcome after pediatric epilepsy surgery. *Epilepsia* 2022;63(8):1956-69. doi:10.1111/epi.17320
- Pasini F, Quintana M, Rodrigo-Gisbert M, Campos-Fernández D, Abaira L, Fonseca E, et al. Predicting seizure recurrence after status epilepticus: a multicenter exploratory machine learning approach. *Seizure* 2025;131:163-71. doi:10.1016/j.seizure.2025.06.019
- Shen F, Lu L, Wu Y, Suo G, Zheng Y, Zhong X, et al. Risk factors and predictors of recurrence of febrile seizures in children in Nantong, China: a retrospective cohort study. *BMC Pediatr* 2024;24(1):420. doi:10.1186/s12887-024-04895-9